Coalition Game Theory in Cognitive Mobile Radio Networks

Pablo Palacios[1(✉)] and Carlos Saavedra[2(✉)]

[1] Departamento de Redes y Telecomunicaciones, Universidad De Las Américas, Quito, Ecuador
pablo.palacios@udla.edu.ec

[2] Department of Electronics and Radio Engineering, Kyung Hee University, Yongin 446-701, South Korea
carlossaavedra@khu.ac.kr

Abstract. In this work, the impact and performance of the Coalition Game Theory applied directly to the detection and decision stages of a Cognitive Radio (CR) system is evaluated. The performance of the Coalitional Game was analyzed in terms of the Probability of detection (P_d) and Probability of false alarm (P_{fa}) versus number of secondary users (SUs). In addition, the detection accuracy and simulation time versus SU were analyzed in a structured network adapted for WiFi and LTE technologies with cognitive parameters. The results were compared using simulation scenarios to obtain data using the theoretical Non-cooperative decision method and the theoretical Centralized decision method. The evaluated system outperformed the other methods in terms of P_d, P_{fa}, detection accuracy and simulation time.

Keywords: Cognitive mobile radio networks · Probability of detection (P_d) · Probability of false alarm (P_{fa}) · Coalition game theory · Spectrum decision · Spectrum sensing

1 Introduction

The Cognitive Radio (CR) technology has attracted more interest in recent years because it provides efficient use of the electromagnetic spectrum [1], jumping between different frequencies and different wireless protocols, demonstrating the potential to meet the spectrum requirements for 5G [2]. In essence, is a radio that adapts its transmission parameters according to the characteristics of the environment in which it operates, detecting and exploiting the available holes in the spectrum. In the medium term, this is the most likely solution for high data rates and mobility that requires the use of higher frequencies. However, one of the most crucial challenges for the practical implementation of CR systems is to constantly identify the presence of primary users (PU) in a wide range of spectrum in a particular time and specific geographic location, in addition to checking that there is no interference between SU (without a license) and PU [3].

M. Botto-Tobar et al. (Eds.): CITT 2018, CCIS 895, pp. 3–15, 2019.
https://doi.org/10.1007/978-3-030-05532-5_1

A fundamental characteristic offered by CR is that it allows total spectrum management through a process called cognitive cycle, which consists of four steps: spectrum detection, spectrum decision, spectrum sharing and mobility [4]. Within the aforementioned cognitive process, studies and research are emphasized in the first two steps, the detection and decision of the spectrum and of licensed users. Therefore, several methods have been proposed, for this work we will focus attention on methods and decision algorithms specifically studied in Game Theory and applied to CR systems, such as Coalition formation through merge and split [5], Evolutionary game [6], Cournot game model [7], among others.

The Game Theory is established as an analytical mathematical tool. The challenges of wireless networks, of an autonomous and dynamic nature, require a decentralized and diverse understanding, as well as design tools to make them more efficient. Cooperative game theory, particularly coalition game theory, is emerging as an appropriate mechanism for flexible and efficient distribution.

The existing literature has studied the performance of Coalition Game in CR networks. This is based on the detection bits of the SUs that share their sensory decisions towards an SU called "head of the coalition" that combines the detection bits of each SU using some rule for the fusion of data. A similar approach is used in [8] using different decision-combination methods. These soft decisions improve performance compared to hard decisions, such as the non-cooperative games or the individual detection and decision of each [9].

The main contribution of this work is to analyze and evaluate the performance and efficiency of the Coalition Game decision method applied, adapted and configured to a mobile radio network with cognitive characteristics, specifically for LTE and WiFi technologies through modules created for Network Simulator 3 (NS-3.23) [10]. The performance of the Coalition Game decision method is analyzed under the next parameters: detection probability (P_d), false alarm probability (P_{fa}), detection accuracy and simulation time versus number of secondary users (SUs) using simulation scenarios with numerical values and compared with the theoretical non-cooperative decision method and the theoretical centralized decision method.

2 System Model

In this article, we evaluate the decision of the spectrum using the Coalition Game decision method in a mobile network implemented specifically for LTE and WiFi with cognitive characteristics, which are state-of-the-art technologies and also basic techniques and algorithms in heterogeneous networks [11–14]. We consider the scenario like a area covered by Cognitive Mobile Radio network composed of m independent source-destination pairs of PU's. The set of primary transmitters is represented as $P_t = (P_{1t}, \ldots P_{mt})$ while the set of corresponding receivers is represented as $P_r = (P_{1r}, \ldots P_{mr})$. We assume the coexistence of n secondary transmitters in set $S_t = (S_{1t}, \ldots S_{nt})$ and their corresponding receivers in set $S_r = (S_{1r}, \ldots S_{nr})$. Here, a "primary channel" refers to a licensed spectrum band currently being utilized by a PU. This scenario is shown in Fig. 1.

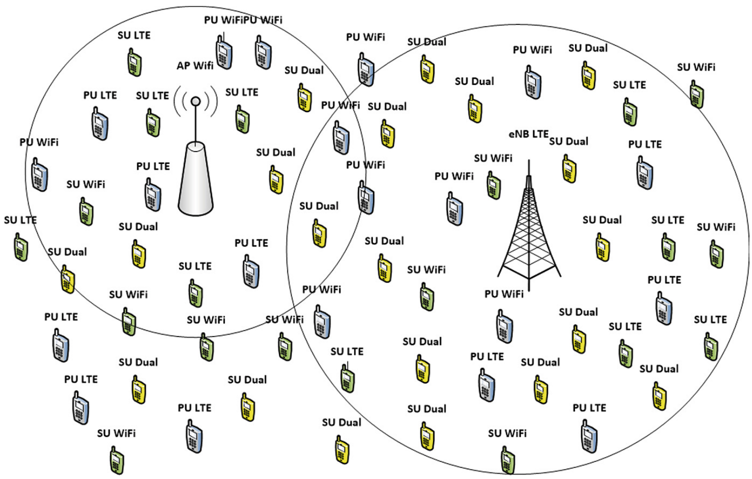

Fig. 1. Proposed system model. This is a network topology that illustrates the system model. It consists of PU (WiFi and LTE) and SU (WiFi, LTE and dual) users that share the same spectral environment, in an area covered by the AP for WiFi technology and the eNB (for LTE technology).

It is assumed that each PU complies with a fixed rate requirement of R_p bps during the entire time interval $[0, T]$ where T is expressed in seconds and that the rate requirement is less than or equal to the maximum capacity of the link between the base station (eNB or AP) and the PU. As well, it is assumed that PUs are assigned orthogonal frequency channels (OFDM), in the frequency of WiFi and LTE technology. The channels between any pair of nodes are modeled as a slow Rayleigh fading being all independent channels. It is assumed that the additive white Gaussian variance noise N_0 is present in each user, both PU and SU.

Following the general assumptions on cooperative spectrum detection, each SU can operate on any of the subchannels that have been licensed for the PUs following the cooperation rules. The decision is made by the head of the coalition by a majority of votes of the members to whom the decision is transmitted and executed immediately. Hence, we can define coalition Ω composed by the set C_Ω of SU. Also, the time interval $[0, T]$ it is divided into two main stages:

1. The *cooperation phase*: In the first fraction α_P of T, the SU in set C_Ω assist the coalition decision. This is done by the head of the coalition based on an election of the majority of the members of the coalition through some pre-established function and is transmitted to all members of the same coalition.
2. The SU *transmission phase*: In the time fraction $(1 - \alpha_P)$ of T, the SU in set C_Ω will share the licensed channel for the PUs and will be able to carry out their transmissions.

3 Problem Formalization and Coalition Game Decision Method Mathematical Model

3.1 Problem Formulation

The spectrum sensing problem can be modeling as a hypothesis of two options testing [15]. This test can be replaced by

$$x(t) = \begin{cases} n(t) & H_0 \\ h(t) * s(t) + n(t) & H_1, \end{cases} \tag{1}$$

where $x(t)$ is the SU signal received, $s(t)$ is the PU signal transmitted, $n(t)$ is the Noise AWGN and $h(t)$ is the channel gain [15]. Here, H_0 and H_1 are the hypothesis of the absence and presence of the PU in the evaluated channel.

In this paper, an SVD detector is chosen as the spectrum sensing technique for its ease of design, implementation and it was also verified that it is more efficient in terms of Probability of detection than other common methods of detection. According to [16], the received signal $x(t)$ will be factorized into a singular values R output by the SVD detector. Then, R is compared with a detection threshold λ to decide on whether the PU is present or not. More information on threshold determination can be found in [16].

The performance of spectrum detection can be primarily described by two basic metrics: Probability of detection (P_d) denoting the probability that a PU is reported to be present when the spectrum is indeed occupied by the PU and Probability of false alarm (P_{fa}) denoting the probability that a PU is declared to be present when the spectrum is actually free.

The cooperative selection and scheduling problem (Detection stage) was formulated as an Coalition game, $G = (N, u)$ where $N = S_1$ U $S_2 \ldots$ U S_n, and $|N| = n$, and u is the payoff function that converts a user contribution into its profit. The method is structured in two stages, The *cooperation phase* and The SU *transmission phase*.

3.2 The *Cooperation Phase*

To better analyze the performance of Coalition Game Method, we start with the local (individual) SVD detection. In an environment where Rayleigh fading predominates, the P_d and P_{fa} of SU i detecting the status of PU/channel j are, respectively, given by $P_{d,i,j}$ and $P_{f,i,j}$ as follows [17]:

$$\begin{aligned} P_{d,i,j} = [PY_{i,j} > \lambda | H_1] = e^{-\frac{\lambda}{2}} \sum_{n=0}^{w-2} \frac{1}{n!} \left(\frac{\lambda}{2}\right)^n + \left(\frac{1+\gamma_{i,j}}{\gamma_{i,j}}\right)^{w-1} \\ * \left[e^{-\frac{\lambda}{2(1+\gamma_{i,j})}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{w-2} \frac{1}{n!} \left(\frac{\lambda * \gamma_{i,j}}{2(1+\gamma_{i,j})}\right)^n \right] \end{aligned} \tag{2}$$

$$P_{fa,i,j} = [PY_{i,j} > \lambda | H_0] = \frac{\Gamma\left(w, \frac{\lambda}{2}\right)}{\Gamma(w)} \tag{3}$$

where λ is the detection threshold for PU j, w is the time-bandwidth product, $Y_{i,j}$ is the normalized output of SU i sensing the status of PU j, and $\gamma_{i,j}$ denotes the average SNR of the received signal from the PU to the SU, which is defined as $\gamma_{i,j} = P_j\ h_{j,i}/\sigma^2$, with P_j being the transmit power of PU j, σ^2 being the Gaussian noise variance and $h_{j,i} = k/d^v_{j,i}$ being the path loss between PU j and SU i; here, k is the path-loss constant, v is the path-loss exponent, and $d_{j,i}$ is the distance between PU j and SU i. $\Gamma(.,.)$ is the *incomplete gamma function*, and $\Gamma(.)$ is the gamma function. Notice that the non-cooperative P_{fa} expression $P_{fa,i,j}$ depends only on the detection threshold λ and doesn't depend on the SU's location.

An important metric is the missing probability P_m for a SU i, which is defined as the probability of not detecting a PU even though it is found and given by

$$P_{m,i,} = 1 - P_{d,i,j} \tag{4}$$

The reduction and increase in efficiency of the missing probability is directly related to the increase in the P_d and, therefore, the interference decrease in the PUs. To diminish the missing probability, the SU will relate to each other under certain parameters to form SU coalitions that collaborate with each other. Within each Ω coalition, an SU, selected as *coalition head*, collects all the SU detection bits that make up the coalition and acts as a merger center in order to make a decision for the whole coalition based on the principle of presence or absence of the PU. This can be seen as having a centralized collaborative detection class of [21,22] applied in the level of each coalition with the head of the coalition being the fusion center to which all members of the coalition inform. For the head of the coalition to make an accurate decision, logical rules such as AND or OR can be used.

In order to obtain a distributed class algorithm that allows maximize the P_d per SU, we refer to cooperative game theory [11] that provides a set of mathematical analysis tools suitable for such algorithms. Thus, the proposed collaborative problem can be structured as a (C_Ω, v) coalitional game [14] where C_Ω is the set of players (the SU's) and v is the utility function or value of a coalition. The value v(Ω) of a coalition $\Omega \subset C_\Omega$ must capture the trade off between the P_d and the P_{fa}. For this purpose, v(Ω) must be an increasing function of the P_d. By collaborative sensing, the missing probability and P_{fa} of each coalition Ω having coalition head k are, respectively, given by:

$$Q_{m,\Omega} = \prod_{i\in\Omega} [P_{m,i} * (1 - P_{e,i,k}) + (1 - P_{m,i}) * P_{e,i,k}], \tag{5}$$

$$Q_{m,\Omega} = 1 - \prod_{i\in\Omega} [(1 - P_{fa}) * (1 - P_{e,i,k}) + P_{fa} * P_{e,i,k}], \tag{6}$$

where P_{fa} , $P_{m,i}$ and $P_{e,i,k}$ are respectively given by [23] for a SU i $\in \Omega$ and coalition head $k \in \Omega$.

A suitable utility function is given by

$$v(\Omega) = Q_{d,\Omega} - C(Q_{f,\Omega}) = (1 - Q_{m,\Omega}) - C(Q_{f,\Omega}), \tag{7}$$

where $(Q_{m,\Omega})$ is the missing probability of coalition Ω and $C(Q_{f,\Omega})$ is a cost function of the false alarm probability within coalition Ω given by:

$$C(Q_{f,\Omega}) = \begin{cases} -\alpha^2.log(1 - \left(\left(\frac{Q_{f,\Omega}}{\epsilon}\right)^2\right) & if\ Q_{f,\Omega} < \epsilon \\ +\infty & if\ Q_{f,\Omega} \geq \alpha, \end{cases} \tag{8}$$

where log is the natural logarithm and ϵ is a false alarm constraint per coalition (per SU). It is important to bear in mind that the proposed cost function depends solely on the distance and the number of SUs in the coalition, through the use in its expression of the $Q_{f,\Omega}$ (the distance lies within the probability of error). Hence, the cost for collaboration increases with the number of SU's in the coalition as well as when the distance between the coalition's SU's increases. Any coalition structure resulting will have coalitions limited in number of users to a maximum of the next expression:

$$M_{max} = \frac{log\,(1-\epsilon)}{log\,(1-P_{fa})} \tag{9}$$

3.3 The SU Transmition Phase

TDMA is assumed, and the transmission is divided in time, based on the SUs contributions in Ω. Therefore, the time allotted for SU is given by $(1-\alpha_P)^{*}t_i^{\Omega}$. Its gain is directly proportional to the amount of energy spent by the SU to assist the coalition head k in the cooperation phase.

3.4 Coalition Formation Algorithm

The proposed algorithm is shown below:

1. **PHASE 1:** Local detection, where each individual SU will obtain its PU signal detection bit, using SVD detection method.
2. **PHASE 2:** Formation of adaptive coalitions, during the formation of the adaptive coalition it is assumed that any SU can randomly start the union process. Coalitions are formed based on the merge and split algorithm indicated below:
   - **Merge:** the coalition decides to merge by following the steps below:
     (a) It is decided to merge any set of coalitions if the utility function of the merge is better compared to each coalition by individual, in addition if the set of coalitions covers all the users of the partition, and by Pareto, it is preferable, given its utility function, compared to uncooled partitions.
     (b) The comparison is realized depending on the following utility function of each CR, shown in Eq. 7.
     (c) In the proposed collaboration detection game, the utility of a coalition S is equal to the utility of each CR user in the coalition.

(d) The probability of detection losses of a PU and the probability of false alert of any CR user that belongs to the coalition are given by the above mentioned probabilities, but of the coalition.
– **Split:** It is decided to separate a set of coalitions if the utility function of each coalition of the set per individual is better than the union of the coalitions.

3. **PHASE 3:** Detection of the coalition, each CR user reports his detection bit to each head of the coalition. The head of each coalition makes a final decision about the presence or absence of a primary user using an OR rule.

4 Detection Accuracy Calculation

In game theory methods, payoff is used to have an estimate tradeoff between reward and penalty. In this research, reward refers to the transmission rate by SU (in case of correct detection indicating that the PU is inactive). Penalty is the loss in the transmission rate due to interference to PU (in case of missing detection). Sensing accuracy is given by A.

$$A = P_d * (T - \delta) - P_{m,i} D_0 (T - \delta) \tag{10}$$

where (T $-$ δ) is the data transmission duration and iδ is the sensing duration.

A network structure example is shown in Fig. 2.

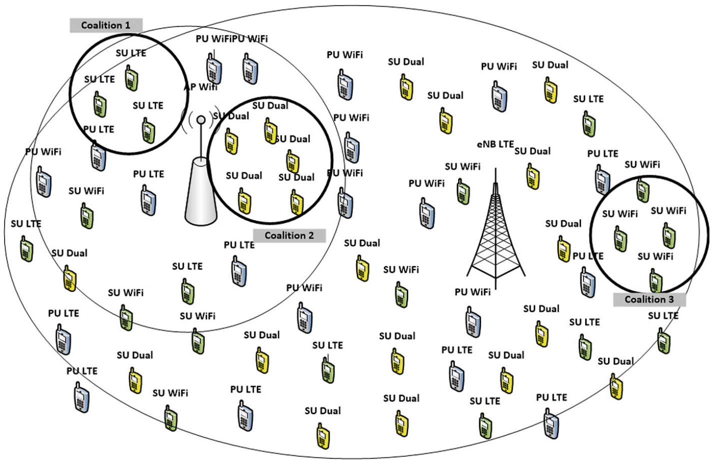

Fig. 2. An illustrative example of coalition formation for collaborative spectrum detection among SU's

5 Simulation Evaluation

5.1 Simulation Setup

A module in Network Simulator 3 (NS-3.23) that contains the four basic stages of a CR system is developed. In our simulation study, we consider a network topology with the following characteristics:

- The propagation models and mobility models are specific to NS-3. The propagation model is the Range Propagation Loss, is a model that depends only on the variable distance (range) between the Tx and the Rx, for our work adapted to the PU and SU with their respective eNB and AP. The single MaxRange attribute (units of meters) determines path loss.
- The mobility model is the Random Waypoint Model.
- Nodes are PU WiFi and PU LTE without cognitive ability (primary UE).
- The LTE and WiFi carrier frequencies are set to 729 MHz and 2400 MHz, respectively.
- The number of SU LTE and WiFi, and the number of dual SUs are variable and the values are between $0, 1, 2, 3, 4, 5, 6, 7, 10, 20, 30$. The PU LTE and WiFi number are set to 10, respectively. The total number of users in the network simulated both CR and primary are chosen, because it is the number of average users that use a WiFi and LTE network.
- The range of coverage of the AP and eNB are set to 200 m and 350 m, respectively. This was done to generate interference between the technologies.

All of the parameters used in the simulation are shown in Table 1. The same parameters were used for each type of decision method, in order to be compared.

5.2 Simulation Results

The (P_d) vs $CR\ users$ and the (P_{fa}) vs $CR\ users$ is presented as a cumulative distribution function (CDF) for all methods compared, as shown in Figs. 3 and 4. The proposed Coalition Decision method curve was obtained implementing and simulating the algorithm in NS-3, whereas the curves of Non-cooperative decision method and Centralized decision method were obtained implementing and simulating using MATLAB.

The P_d parameter of each simulation was obtained by dividing all the samples of each simulation where the detection was 1 (detected), for the number total of samples and the P_d parameter for each number of CR users was obtained by dividing the sum of all the P_d of each simulation for the number of simulations performed (21).

Figure 4 shows that the average obtained from P_{fa} for the solution proposed based on coalitions exceeds the performance of the centralized solution with which it was compared, but it is still lower than the solution based on a non-cooperative case. Therefore, the proposed algorithm compensates for this performance gap through the false average alarm reached. In summary, Figs. 3 and 4 show the performance trade off that exists between the gains achieved by

Table 1. System simulation parameters

Parameter	Value
LTE frequency	729 MHz
eNB cells	3
WiFi frequency	2400 MHz
LTE bandwidth	20 MHz
WiFi bandwidth	20 MHz
Tx power	0.037 mW
Rx power	0.06 mW
CR LTE UE	Variable
CR WiFi UE	Variable
Dual CR UE	Variable
Primary LTE UE	10
Primary WiFi UE	10
AP range of coverage	200 m
eNB range of coverage	350 m
Time of simulation	1200 s
Samples	16000
Traffic	TCP
Mobility model	Random Waypoint
Propagation model	Range Propagation Loss

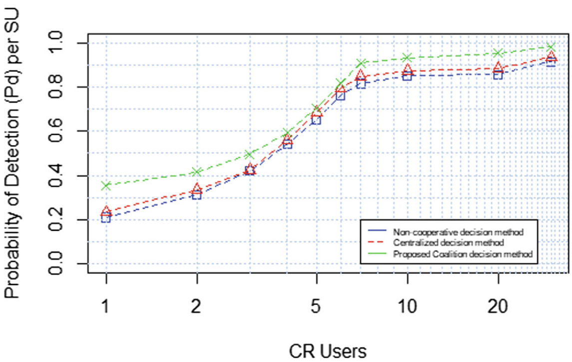

Fig. 3. Probability of detection of several methods vs. number of SU's.

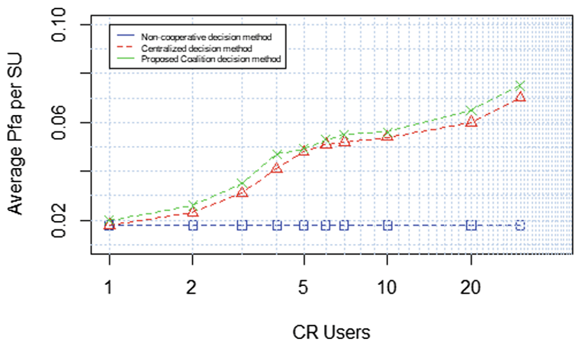

Fig. 4. Average false alarm probabilities of several methods vs. number of SU's.

collaborative detection through the game of coalitions in terms of the average missing probability and the cost in terms of average false alarm probability.

Figure 5 shows a detection accuracy diagram with respect to the SU number variation. If the amount of SU increases, the chances of having a Improvement in the channels to detect increases and thus also increases detection accuracy.

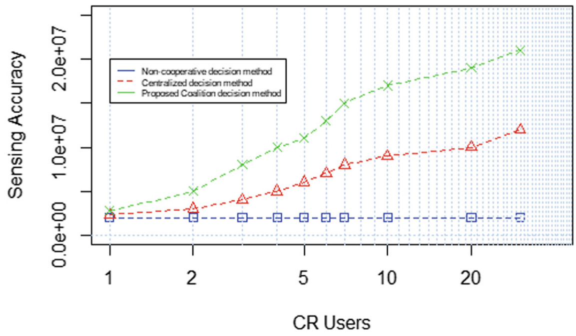

Fig. 5. Sensing accuracy of several methods vs. number of SU's.

Before performing the experiments, we must take into account an important factor for the simulator, that the simulation time is not the same as the real time. For this purpose, several simulations were carried out with different simulation times, maintaining the basic technical parameters without modifying which are indicated in Table 1, in order to observe the behavior of the real time.

The number of simulations was defined using the Monte Carlo method, with 21 iterations for each value of SU, this is to have reliable estimates in the distributions of the generated data [31,32].

We observe the linear and increasing behavior of Real Time vs Simulation time in Fig. 6.

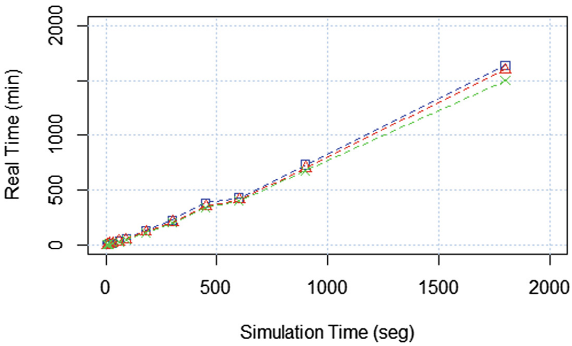

Fig. 6. Simulation time vs. real time

6 Conclusions

In this paper, we propose a collaborative spectrum detection method applied to cognitive mobile radio networks. We modeled the collaborative problem of decision and detection as a coalition game provided by mathematical tools of Game Theory, with a utility function and we obtained an algorithm for the formation of coalitions of SUs. The proposed coalition formation algorithm is based on the merge and split rules that allow the SUs that make up the coalitions in a cognitive mobile network to cooperate with each other to improve their P_d having as a limitation the cost in terms of P_{fa}. We characterize simulation scenarios with resulting network structures implementing the proposed algorithm in each of the nodes, analyze their performance and efficiency. In addition, the parameters of sensing accuracy and simulation time are observed. Simulation results showed that the proposed algorithm increase the P_d, P_{fa}, sensing accuracy and decrease the simulation time per SU compared to the non-cooperative case and the centralized case. The results showed that through the proposed efficient detection and decision algorithm, the SU can adapt and change the structure of the network autonomously and intelligently, if there are variations of parameters that can be environmental, power, distance, etc.

References

1. Ramani, V., Sharma, S.K.: Cognitive radios: a survey on spectrum sensing, security and spectrum handoff. Chin. Commun. **14**(11), 185–208 (2017)
2. Hu, F., Chen, B., Zhu, K.: Full spectrum sharing in cognitive radio networks toward 5G: a survey. IEEE Access **PP**(99), 1 (2018)
3. Luís, M., Oliveira, R., Dinis, R., Bernardo, L.: RF-spectrum opportunities for cognitive radio networks operating over GSM channels. IEEE Trans. Cogn. Commun. Netw. **3**(4), 731–739 (2017)
4. Wang, J., Feng, S., Wu, Q., Zheng, X., Xu, Y.: Hierarchical cognition cycle for cognitive radio networks. Chin. Commun. **12**(1), 108–121 (2015)

5. Saad, W., Han, Z., Basar, T., Debbah, M., Hjorungnes, A.: Coalition formation games for collaborative spectrum sensing. IEEE Trans. Veh. Technol. **60**(1), 276–297 (2011)
6. Wang, B., Liu, K.J.R., Clancy, T.C.: Evolutionary cooperative spectrum sensing game: how to collaborate? IEEE Trans. Commun. **58**(3), 890–900 (2010)
7. Niyato, D., Hossain, E.: A game-theoretic approach to competitive spectrum sharing in cognitive radio networks. In: 2007 IEEE Wireless Communications and Networking Conference, Kowloon, pp. 16–20 (2007)
8. Peh, E.C.Y., Liang, Y.C., Guan, Y.L., Zeng, Y.: Cooperative spectrum sensing in cognitive radio networks with weighted decision fusion schemes. IEEE Trans. Wirel. Commun. **9**(12), 3838–3847 (2010)
9. Chaudhari, S., Lunden, J., Koivunen, V., Poor, H.V.: Cooperative sensing with imperfect reporting channels: hard decisions or soft decisions? IEEE Trans. Sig. Process. **60**(1), 18–28 (2012)
10. ns-3 Model Library, Release ns-3.23. https://www.nsnam.org/docs/release/3.23/models/ns-3-model-library.pdf
11. Li, H., et al.: Utility-based cooperative spectrum sensing scheduling in cognitive radio networks. IEEE Trans. Veh. Technol. **66**(1), 645–655 (2017)
12. Abuzainab, N., Vinnakota, S.R., Touati, C.: Coalition formation game for cooperative cognitive radio using Gibbs sampling. In: 2015 IEEE Wireless Communications and Networking Conference (WCNC), New Orleans, LA, pp. 937–942 (2015)
13. Fenila Janet, M., Lavanya, S., Bhagyaveni, M.A.: Performance analysis of cooperative spectrum sensing in cognitive radio using game theory. In: 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, pp. 2061–2065 (2016)
14. Hyder, C.S., Xiao, L.: Cooperative routing via overlapping coalition formation game in cognitive radio networks. In: 2016 25th International Conference on Computer Communication and Networks (ICCCN), Waikoloa, HI, pp. 1–6 (2016)
15. Palacios, P., Castro, A., Azurdia-Meza, C., Estevez, C.: Signal detection methods in cognitive mobile radio networks: a performance comparison. In: IEEE Latin-American Conference on Communications (LATINCOM), 2017 Workshop, Guatemala (2017)
16. Palacios, P., Castro, A., Azurdia-Meza, C., Estevez, C.: SVD detection analysis in cognitive mobile radio networks. In: 2017 Ninth International Conference on Ubiquitous and Future Networks (ICUFN), Milan, pp. 222–224 (2017)
17. Mathur, S., Sankaranarayanan, L., Mandayam, N.: Coalitions in cooperative wireless networks. IEEE J. Sel. Areas Commun. **26**, 1104–1115 (2008)
18. Han, Z., Liu, K.J.: Resource allocation for wireless networks: basics, techniques, and applications. Cambridge University Press, Cambridge (2008)
19. Shiryaev, A.N.: On optimum methods in quickest detection problems. Theory Probab. Appl. **8**(1), 22–46 (1963)
20. Saad, W., Han, Z., Debbah, M., Hjørungnes, A., Başar, T.: Coalitional games for distributed collaborative spectrum sensing in cognitive radio networks. In: Proceedings of IEEE INFOCOM, Rio de Janeiro, Brazil, April 2009
21. Foster, I., Kesselman, C.: The Grid: Blueprint for a New Computing Infrastructure. Morgan Kaufmann, San Francisco (1999)
22. Owen, G.: Game Theory, 3rd edn. Academic, London (1995)
23. Czajkowski, K., Fitzgerald, S., Foster, I., Kesselman, C.: Grid information services for distributed resource sharing. In: 10th IEEE International Symposium on High Performance Distributed Computing, pp. 181–184. IEEE Press, New York (2001)

24. Foster, I., Kesselman, C., Nick, J., Tuecke, S.: The physiology of the grid: an open grid services architecture for distributed systems integration. Technical report, Global Grid Forum (2002)
25. National Center for Biotechnology Information. http://www.ncbi.nlm.nih.gov
26. Ghasemi, A., Sousa, E.S.: Collaborative spectrum sensing for opportunistic access in fading environments. In: IEEE Symposium New Frontiers in Dynamic Spectrum Access Networks, Baltimore, USA, pp. 131–136, November 2005
27. Visotsky, E., Kuffner, S., Peterson, R.: On collaborative detection of TV transmissions in support of dynamic spectrum sensing. In: IEEE Symposium New Frontiers in Dynamic Spectrum Access Networks, Baltimore, USA, pp. 338–356, November 2005
28. Niyato, D., Hossein, E., Han, Z.: Dynamic Spectrum Access in Cognitive Radio Networks. Cambridge University Press, Cambridge (2009)
29. Myerson, R.: Graphs and cooperation in games. Math. Oper. Res. **2**, 225–229 (1977)
30. Saad, W., Han, Z., Debbah, M., Hjørungnes, A.: Network formation games for distributed uplink tree construction in IEEE 802.16j networks. In: Proceedings of IEEE Global Communication Conference, pp. 1–5, New Orleans, LA, December 2008
31. Alfonso, U.M., Carla, M.V.: Modelado y simulación de eventos discretos. Editorial UNED (2013)
32. Ramírez, I.C., Barrera, C.J., Correa, J.C.: Efecto del tamañoo de muestra y el número de réplicas bootstrap. Ingeniería y Competitividad **15**(1), 93–101 (2013)